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Published in:
Energy Conversion & Management

DOI:
[10.1016/j.enconman.2019.112021](https://doi.org/10.1016/j.enconman.2019.112021)

Published: 01/11/2019

Document Version
Peer reviewed version

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Please cite the original version:
Khosravi, A., Syri, S., Garcia Pabon, J. J., R. Sandoval, O., Castro Caetano, B., & H. Barrientos, M. (2019). Energy Modeling of a Solar Dish/Stirling by Artificial Intelligence Approach. *Energy Conversion & Management*, [112021]. <https://doi.org/10.1016/j.enconman.2019.112021>

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Energy Modelling of a Solar Dish/Stirling by Artificial Intelligence Approach

Ali Khosravi¹, Sanna Syri¹, Juan J. Garcia^{2*}, Oscar R. Sandoval³, Bryan Castro Caetano³, Miguel H. Barrientos³

¹Department of Mechanical Engineering, School of Engineering, Aalto University, Finland

²Institute of Mechanical Engineering, Federal University of Itajubá, Brazil

³Programa de Pós-graduação em Engenharia Mecânica, Universidade Federal de Minas Gerais, Brazil

* Corresponding author: jjgp@unifei.edu.br

Abstract

Solar energy is a renewable energy resources that is available across the world. A solar dish/Stirling system means a parabolic dish concentrator and a Stirling engine combined to generate mechanical and/or electrical output power. In this system, the input energy of Stirling engine is provided by sunlight as a source of heat. This study presents the effect of different variables on the power generation and efficiency of the system. In addition, artificial intelligence approach is employed to model a solar dish/Stirling system. For this target, a huge dataset was provided by considering a wide range of input variables. The intelligent methods are group method of data handling (GMDH) type neural network, adaptive neuro-fuzzy inference system (ANFIS) and multilayer perceptron (MLP) neural network (ANN). The MLP and ANFIS are optimized with particle swarm optimization (PSO) and genetic algorithm (GA). The intelligent methods are trained with inputs and targets. The considered input parameters are the ratio of focal point to dish diameter, hour of day, solar radiation, geometric concentration factor and working gas specific constant. The power generation, global efficiency, heat used to run the Stirling cycle, hot Stirling chamber temperature and engine speed are selected to be the targets. The results depict that the intelligent methods operate successfully for energy modeling of the solar dish/Stirling system and the statistical indicators illustrate that the ANFIS-PSO method performs better than the other developed methods.

Keywords: Solar dish/Stirling system; Particle swarm optimization; Genetic algorithm; Adaptive neuro-fuzzy inference system; Artificial neural network; Energy modeling

1. Introduction

Carbon dioxide (CO₂) emissions need to be increasingly restricted to combat global warming [1]. To achieve the reduction of CO₂ release, it is also necessary to reduce the consumption of non-renewable fuels [2,3]. In addition to wind energy development, solar energy, also combined with external combustion engines, is strong candidate for transforming solar radiation into mechanical and electrical energy [4]. The Stirling engine emerged in 1816 as an alternative to solve the serious accidents occurred with generation plants where was operated steam engines, for their ability to work with external combustion at low pressures [5]. Among the main points that make the Stirling engine a viable alternative as a "clean" thermal engine are: low maintenance cost due to its mechanical simplicity [6]; considerably high lifetime, close to 10 years [7]; low levels of noise and pollutant emissions [8]; ability to operate with the most different types of heat source [9–11], including residual heat [12]; high thermal efficiency at partial loads, around 30% [10,13]; and the theoretical efficiency close to the Carnot efficiency due to its reversibilities [14]. The real thermal

38 performance of the Stirling engine cycle is lower than ideal efficiency due to the fact that problems such as
 39 heat transfer resistance, gas leaks and heat losses[15]

Nomenclature	
A_{ir} available dish area [m ²]	P_{lim} pressure limit [Pa]
A_r receiver area [m ²]	P_m working pressure [Pa]
A_s Stirling engine shadow area [m ²]	Pr Prandtl number
A_{TT} receiver heat exchange total area [m ²]	Q heat loss [W]
C geometric concentration factor	R_b ratio of direct irradiation on the horizontal surface
C_{pr} specific heat [J/(kgK)]	T temperature [K]
e receiver wall thickness [m]	T^* Iwamoto's dimensionless temperature
d Stirling engine diameter [m]	V_{SE} expansion swept volume [m ³]
f focus [m]	W_s West number
f_A Martini's constant	W_s^* dimensionless output power
G_{sc} Solar constant [W/m ²]	z support displacement [m]
H receiver height [m]	α absorptance
h heat transfer coefficient [W/(m ² K)]	ω average hour time in degrees [°]
I solar radiation [W/(m ²)]	RN Rio Grande do Norte
L^* :Iwamoto's dimensionless output power	ϵ material emissivity
L_s :Stirling engine output power [W]	η efficiency
m_r receiver material mass [kg]	κ receiver thermal conductivity, [W/(m K)]
n engine speed, [rps]	μ dynamic viscosity, [Pa.s]
n_{day} day	ν kinematic viscosity of the fluid [m ² /s]
Nu Nusselt number	δ solar declination angle [°]
P_c circular surface power [W]	ϕ : latitude [°]
P_{cy} cylindrical surface power [W]	

40 Solar energy has been quite attractive because it is a clean source of energy, efficient and economically
 41 viable [16] when compared to other solar concentration technologies such as chimney [17], line-focusing
 42 [18] and tower [19], the parabolic dish [20] is the one with the highest efficiency and the most practical
 43 implementation for solar tracking [21]. This makes dish/Stirling systems achieve high efficiency in electric
 44 generation and can achieve power in the range of 1 to 100 kW [22]. The performance of a parabolic dish is
 45 directly proportional to the accuracy of its components, with a flow distribution in the well-sized focal
 46 region, the parabolic dish can produce high temperatures at a high efficiency [23,24]. Therefore, the analysis
 47 of the flux distribution must be seriously studied so that heat losses at the receiver, heat losses by natural
 48 convection and radiation losses are minimized [25]. Another important point is the use of mathematical
 49 models to predict the solar characteristics of a locality, with which it is possible to perform the study of the
 50 radiation available to a dish/Stirling system [26,27].

51 On the combination of Stirling engines with solar concentrators, numerous approaches have already been
 52 performed to analyze the performance of the set. Chen et al. [28] studied the optimal temperature of Stirling
 53 engine installed in a parabolic dish by means of a finite-time thermodynamic modeling with irreversibilities
 54 of conduction of heat and regenerative losses; with the same modeling, Liao and Lin [29] analyzed the
 55 optimum efficiency as a function of concentration ratio of dish, volume ratio of Stirling engine and
 56 irreversibilities in the heat transfer; Beltran et al. [30] demonstrated that the thermal efficiency of a
 57 concentrator disk undergoes small variations according with the temperature, wind speed, solar irradiance
 58 and the position by mathematical model; Maghrabi [26] and Zhang et al. [27] presented a comprehensive
 59 review of models that provide reliable results for solar technology design and development.

On the other hand, several approaches were carried out using intelligent methods in Stirling engines as well as parabolic concentrators [31–33]. Among them, two methods stand out, the Group Method of Data Handling-Type Neural Network (GMDH) is a self-organizing approach based on assessing its effectiveness for a variety of data pairs of different unique inputs and outputs [34]. The Adaptive Neuro-Fuzzy Inference System (ANFIS) is a hybrid technique that use artificial neural networks (ANN) to perform the learning and fuzzy inference system to compensate the disadvantage of the neural network where the weight values cannot be explained [35]. Some investigations present algorithms for the modeling of Stirling engine characteristics; Ahmadi et al. [49] developed an algorithm including GMDH method to predict power and torque in a Stirling engine. Özgören et al. [36] with the aid of ANN, presented a model of performance of the Stirling engine that operates pressurized with helium, thus allowing the calculation of parameters such as power and efficiency. Ahmadi et al. [37] using the least square support vector (LSSVM) method, with reasonable accuracy estimated the power and torque generated by a Stirling engine. In solar researches, learning algorithms are also widely used to predict solar characteristics and performance of concentrator dishes by Loni et al. [38]. Alata et al. [39] developed a diffuse control solar tracking system using ANFIS to maximize the radiation incident on a surface. Loni et al. [38] present an ANN model for a parabolic dish with a tubular receiver.

Modeling of a solar dish/Stirling system under various operating conditions can be undertaken through intelligent methods, so the cost and time spent on experimental testing are drastically reduced. In many conditions, the process can be complex, with a large number of variables potentially affecting the targets. Besides, however, most manufacturers still use the conventional statistical process control methods which exert univariate statistical approach in their analysis. Oftentimes, the univariate statistics are not successful in catching the fundamental patterns in data processing. This is where artificial intelligence methods can provide a multivariate processing approach for intricate engineering problems, specifically for energy modeling of a solar dish/Stirling system. Based on the literature, it can be found out that learning methods through a computational algorithm can obtain the optimum operating conditions, geometries, economic feasibility and energy characteristics of renewable energy systems. In this study, four hybrid methods including ANFIS-PSO, ANFIS-GA, MLP-PSO and MLP-GA are developed for energy modeling of a solar-powered Stirling engine system in Natal-RN, Brazil. The hybrid methods are compared with GMDH method that has been widely used in the literature. Indeed, the main contribution of this work is to develop an accurate and reliable method of AI to energy modeling of the system. We demonstrate which model is more accurate to catch the complex nonlinear pattern between the various input parameters and targets. In addition, this study for the first time proposes a network that can be used instead of the energy mathematical model for solar dish/Stirling system. Furthermore, despite many studies on renewable energy systems, no study has yet been reported in the literature on examining the performance of the hybrid intelligent methods.

2. Case Study

For being located in a tropical region, Brazil is favored in solar energy resources. Thus, high rates of solar radiation with low variability are common throughout the year. Fig. 1 shows the global and the direct radiation on horizontal surface, highlighting the high values of the northeast region, which even surpasses

northern countries where the harnessing of solar energy is widely used [40]. Located in the Brazilian northeast region, Natal-RN has the highest solar radiation of the country (2015 kWh/m².year), which makes it an interesting station regarding the use of available solar energy. Collected by the Brazilian program SONDA in 2015, Fig. 2 depicts the direct normal irradiance for the study region [41].

Fig. 1. Brazilian long term average of global horizontal irradiance [42].

Fig. 2. The direct normal solar radiation data for Natal-RN collected by the SONDA in 2015.

3. Solar Dish/Stirling System

3.1. Solar Model

Using the SONDA database, the direct radiation on the sloped surface (I_{bt}) is achieved through the diffuse radiation (I_d), the direct normal radiation (I_b) and the declination angle (δ) (Eq. (1)), which depends on the evaluated day (n_{day}) [43].

$$\delta = 23.45 \sin\left(360 \frac{284 + n_{day}}{365}\right) \quad (1)$$

111 The hourly extraterrestrial radiation (I_0) is given by Eq. (2) and the cloud distribution coefficient (k_T) is
 112 determined by Eq. (3) using the experimental radiation on the horizontal surface (I_{db}).

$$I_0 = \frac{12G_{SC}}{\pi} \left[1 + 0.033 \cos\left(\frac{360n_{day}}{365}\right) \right] \times \left[\cos(\phi) \cos(\delta) [\sin(\omega_2) - \sin(\omega_1)] + \frac{\pi(\omega_2 - \omega_1)}{180} \sin(\phi) \sin(\delta) \right] \quad (2)$$

113 Where G_{SC} is the solar constant, ϕ is the Natal-RN latitude (-5.78333) and ω_1 and ω_2 define the calculation
 114 time step.

$$k_T = \frac{I_{db}}{I_0} \quad (3)$$

115 Direct radiation on a horizontal surface (I_b) is calculated with the Erbs correlation (Eq. (4)) and the diffuse
 116 radiation (Eq. (5)). Direct radiation on titled surface (I_{bt}) (Eq. (6)) use the ratio of direct radiation (R_b)
 117 given by Eq. (7) [43],

$$\frac{I_d}{I_{db}} = \begin{cases} 1.0 - 0.09k_T & \text{for } k_T \leq 0.22 \\ 0.9511 - 0.1604k_T + 4.388k_T^2 & \text{for } 0.22 < k_T \leq 0.80 \\ -16.638k_T^3 - 12.336k_T^4 & \text{for } k_T > 0.80 \\ 0.165 & \end{cases} \quad (4)$$

$$I_b = I_{db} - I_d \quad (5)$$

$$I_{bt} = I_b R_b \quad (6)$$

$$R_b = \frac{\sqrt{[1 - \cos^2(\delta) \sin^2(\omega)]}}{\sin(\phi) \sin(\delta) + \cos(\phi) \cos(\delta) \cos(\omega)} \quad (7)$$

118 where $\omega = (\omega_1 - \omega_2)/2$ [34].

119 The software MATLAB® is used to program the solar model and to calculate the direct radiation
 120 component used as an input condition to the parabolic dish model.

121 3.2. Parabolic dish

122 Systems that concentrate solar radiation have an operation principle considered simple, since the direct
 123 radiation that reaches the parabolic dish area is concentrated in a smaller area. A dish/Stirling system uses
 124 the solar energy in a concentrated point to provide useful heat for a Stirling engine [4,5,21]. Fig. 3 shows
 125 the system studied in this research, in which, the parabolic dish parameters are rim angle (Ψ), diameter (D),
 126 focus (f) and the support displacement (z). The parameters of cylinder Stirling engine are height (H) and
 127 diameter (d). In this research, the geometric concentration factor is analyzed from 3000 to 12000 and the
 128 ratio f/D changes in three configurations: 0.50, 0.65 and 0.80. The f/D values are stipulated based on
 129 commercial dishes such as General Electric PDC-1 and Acurex 15-m Dish Concentrator both with f/D
 130 equal to 0.5 and Schlaich, Bergermann und Partner 17-m Single-Facet Concentrator with f/D equal to 0.8
 131 [56]. In this work, f/D equal to 0.65 is also studied to analyze a mean condition. The Stirling engine has a
 132 fixed geometry: $d = 0.07$ m, $H = 0.0835$ m, wall thickness of the receiver, $e = 0.001$ m, $A_s =$

0.1627 m². Once the receiver area is fixed, the parabolic dish diameter is a consequence of changes in the geometric concentration factor value, this is, values from 3000 to 12000 correspond to commercial dishes with diameters from 3.8 m to 7.7 m respectively. Dish with 3.8 m represents a low-cost dish as described by the ref. [16] and dish with 7.5 m represents a commercial one as Schlaich, Bergermann und Partner 7.5-m Single-Facet concentrator as described by the ref. [56]. A thermal analysis of the parabolic dish is carried out to calculate the power accumulated on the receiver. The Tonatiuh software that was developed based on the Monte Carlo Ray Tracing method uses a reflectance of 0.82.

Fig. 3. Dish/Stirling system [44].

3.3 Receiver thermal model

The receiver wall temperature is determined by the energy balance in the expansion chamber of the Stirling engine, it is used as an input to the Stirling cycle model for the engine power and thermal efficiency calculation. Fig. 4 presents a schematic of the receiver. The receiver energy balance is described in Eq. (8) [45].

$$m_r c_{pr} \frac{dT_H}{dt} = S - Q_R - Q_C - Q_E \quad (8)$$

In Eq. (8), m_r and $c_{pr} = 460 \text{ J/kg K}$ are the mass and the specific heat of the receiver, respectively. Q_R and Q_C are the radiation and convection heat losses, respectively. Q_E is the Stirling cycle input heat. S is the receiver surfaces power.

$$S = \alpha(P_c + P_{cy}) \quad (9)$$

where the cylindrical surface power (P_{cy}), circular surface power (P_c) are provided by the Tonatiuh simulation and $\alpha = 0.9$ is the material absorptance.

The receiver heat transfer to the environment are calculated by Eqs. (10) and (11),

$$Q_R = A_{TT} h_R (T_H - T_a) \quad (10)$$

$$Q_C = A_{TT} h_C (T_H - T_a) \quad (11)$$

153 in which A_{TT} is the receiver heat exchange total area, T_a is the ambient temperature and T_H is the Stirling
 154 engine expansion chamber temperature. h_R is the heat transfer coefficient due to the radiation (Eq.12).

$$h_R = \sigma \epsilon (T_H - T_a)(T_H^2 + T_a^2) \quad (12)$$

155 where, σ is the Stefan-Boltzmann's constant and $\epsilon = 0.9$ is the material emissivity.

156 The heat transfer coefficient by convection (h_C) is calculated from Eq. (13).

$$h_C = \frac{\kappa Nu}{H + e} \quad (13)$$

157 In which, κ is the receiver thermal conductivity and Nu is the Nusselt number obtained by Popiel method
 158 [46].

Fig. 4. Schematic of the receiver [44].

161 To solve the receiver energy balance, a Stirling engine prediction model is necessary using the
 162 thermodynamic characteristics. For this, an initial value for T_H is approximated and S is determined by
 163 iterative process.

164 3.2. Stirling engine - Iwamoto's modified model

165 Once it is widely presented in the literature, the Stirling engine NS03T was chosen to be studied in this
 166 work.[37,44]. Iwamoto's modified model is composed by Eq. (14) to Eq. (20), which relate the Stirling
 167 shaft power to attributes of the working fluid such as: fluid type, working pressure, compression and
 168 expansion temperatures and also some dimensionless numbers such as: Pressure (P^*), temperature (T^*),
 169 speed (n^*), engine specification (S^*), output power (L^*), output work (W_s^*) and West number (W_S) [44].

$$P^* = \frac{P_m}{P_{lim}} \quad (14)$$

$$T^* = \frac{T_H - T_C}{T_H + T_C} \quad (15)$$

$$S^* = \frac{T_H R V_{SE}^{2/3}}{v^2} \quad (16)$$

$$n^* = 3 \times 10^{-6} S^{*0.6855} \quad (17)$$

$$L^* = 0.0262n^{*1.1982} \quad (18)$$

$$W_S^* = \frac{L^*}{n^*} \quad (19)$$

$$W_S^* = \frac{W_S}{P_m V_{SE} P^* T^*} \quad (20)$$

170 P_m is the working pressure, P_{lim} is the maximum mean pressure, T_H is the expansion chamber temperature,
 171 T_C is the compression chamber temperature, V_{SE} is the expansion swept volume and n is the engine speed
 172 in rps. W_S is calculated by Eq. (21) [47] and ν is the fluid kinetic viscosity at temperature T_H and pressure
 173 P_m , defined by Eq. (22),

$$W_S = \frac{L_S}{P_m V_{SE} n T^*} \quad (21)$$

$$\nu = \frac{Pr_a R T_H^{(1+\mu_b)}}{P_m} \quad (22)$$

174 in which L_S is the engine shaft power, Pr_a is the Prandtl number, μ_b is the working fluid dynamic viscosity
 175 at P_m and T_H and R is the gas constant of fluid.

176 **4. Intelligent Methods**

177 Figure 5 illustrates the proposed network for energy and thermal simulation of the solar dish/Stirling
 178 system. As can be observed in the figure, the network is established by considering the input variables and
 179 targets for a solar-powered Stirling engine system. The inputs are hour of day, the ratio of focal point to
 180 dish diameter (f/d), geometric concentration factor (CR), working gas specific constant ($R_{gas}, J/kg\ K$)
 181 and solar radiation (W/m^2). The power generation, global efficiency, heat transfer from dish to Stirling
 182 engine, expansion chamber temperature of Stirling engine, and speed of Stirling engine are considered as
 183 the target for the network. The next step is to divide the all database (inputs and outputs) in two segments
 184 as train sample (70%) and test sample (30%). Five intelligent methods are developed for this modeling that
 185 the performance prediction of them is evaluated by utilizing three statistical indicators and the best model
 186 is distinguished. The proposed network can be easily employed by each AI method for the energy and
 187 thermal modeling of the solar dish/Stirling system as the data and descriptions have been brought in the
 188 current study.

Fig. 5. The proposed intelligent network for energy and thermal modeling of the solar Stirling system.

4.1. GMDH Method

The group method of data handling (GMDH) neural network was recognized as a self-organizing approach by Ivakhnenko [48]. GMDH is used for estimation and pattern recognition of complicated phenomena/problems; a comprehensive investigation was implemented in [49]. The method has several layers with independent nodes. The nodes are calculated by the quadratic polynomial functions using the previous nodes [50].

4.2. ANFIS Methods

ANFIS is a hybrid of neural networks and fuzzy systems that is composed by fuzzification, inference engine and defuzzification [51]. To obtain the structure of a fuzzy logic system automatically, the artificial neural networks (ANNs) are used and this combination is called neuro-fuzzy system. For being less computationally exhaustive and more transparent than other models, the Sugeno-Takaki model is commonly used (Eqs. (23) and (24)). Radial basis function neural network is applied to incorporate with Sugeno-Takaki type fuzzy system. An ANFIS structure, for simplicity, with only two inputs and one output is indicated in Fig. 6.

Rule 1: If x is A_1 and y is B_1 , then $f_1 = p_1x + q_1y + r_1$ (23)

Rule 2: If x is A_2 and y is B_2 , then $f_2 = p_2x + q_2y + r_2$ (24)

Fig. 6. The structure of an ANFIS with two inputs, one output and two rules.

The ANFIS model has five layers. Layer 1 is named fuzzification layer, the output of each node is [52]:

$$O_i^1 = \exp \left\{ - \left[\left(\frac{x - c_i}{a_i} \right)^2 \right]^{b_i} \right\}, \quad i = 1, 2 \quad (25)$$

In which x is the input and $\{a_i, b_i, c_i\}$ are premise parameters.

Layer 2 is the rule layer; a fixed node calculating the firing strength w_i of a rule.

$$O_i^2 = w_i = \mu_{A_i}(x) \cdot \mu_{B_i}(y), \quad i = 1, 2 \quad (26)$$

In the normalization layer, Layer 3, the fixed node calculates the ratio of the rule's firing strength to the sum of all rules' firing strengths:

$$O_3^i = \bar{w}_i = \frac{w_i}{w_1 + w_2}, \quad i = 1, 2 \quad (28)$$

212 The next layer is the defuzzification layer, every node is an adaptive node calculated by:

$$O_4^i = \bar{w}_i f_i = \bar{w}_i (p_i x + q_i y + r_i), \quad i = 1, 2 \quad (29)$$

213 In which $\bar{w}_i$ is the output of Layer 3 and $\{p_i, q_i, r_i\}$ are the consequent parameters.

214 Layer 5 is the output layer, the node sum of all signal obtained from the previous layer.

$$O_5^i = \sum_i \bar{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i}, \quad i = 1, 2 \quad (30)$$

215 Here, five steps for implementing the hybrid ANFIS methods employing to model the solar dish/Stirling
 216 system are presented. In the process, the inputs and targets are loaded and divided into the training and
 217 testing samples. The initial fuzzy inference system (FIS) is generated. The fuzzy inference system is created
 218 in Matlab software, using fuzzy c-means (FCM) clustering. In the last step, the model is trained with Particle
 219 Swarm Optimization (PSO) or Genetic Algorithm (GA). The optimization problem of FIS is to find the
 220 optimum values $(P_1^*, P_2^*, \dots, P_n^*)$ from basic parameters $(P_1^0, P_2^0, \dots, P_n^0)$. Determining the best value of x in
 221 the Eq. (31).

$$P_i^* = x_i P_i^0 \quad (31)$$

222 4.2. Particle Swarm Optimization (PSO)

223 Particle swarm optimization is employed to find the best solution in optimization problems. The behavior
 224 of birds, insects, and fish communication was the inspiration for model development [53]. A number of
 225 particles is applied to create a swarm moving around the search space to find the best solution. The flying
 226 of each particle in the search space is adjusted based on its own flying experience and the flying experience
 227 of other particles. This process is initiated by generating the initial particles and evaluating their initial
 228 velocities. Fig. 7 denotes the structure of PSO algorithm. As can be observed in Fig. 7, PSO algorithm
 229 follows three main stages as: the optimization target, Global best value and stop condition [54].

230
231 **Fig. 7.** Structure of particle swarm optimization.

4.3. MLP Methods

Feed-forward multilayer perceptron (MLP) was used as structure of ANN. The relation between input (X), weight (W), bias (b) and output (n) is shown in Eq. (32) [55]:

$$n = W_{1,1}X_1 + W_{1,2}X_2 + \dots + W_{1,r}X_r + b \quad (32)$$

However, multilayer neural network is suggested for complex problems. Eqs. (33)- (35).

$$a^1 = f^1(IW^{1,1}X + b^1) \quad (33)$$

$$a^2 = f^2(LW^{2,1}a^1 + b^2) \quad (34)$$

$$a^3 = f^3(LW^{3,2}a^2 + b^3) \quad (35)$$

Where a , IW and LW are layer output vector, input weight matrix and hidden weight matrix, respectively. The MLP-PSO algorithm is divided into 7 stages. Stages 1-4 are data loading, normalization, determining the train and test data and network structure, respectively. In stage 5 of the MLP, the optimum values of weight matrixes (IW and LW) and bias vector (b) are found using PSO or GA algorithm.

The performance of the intelligent method is estimated with three statistical metrics: root mean square error (RMSE, Eq. (36)), correlation coefficient (R, Eq. (37)) and determination coefficient (R^2 , Eq. (38)). During the process of network training, the objective is to obtain the minimum RMSE.

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (x_i - y_i)^2} \quad (36)$$

$$R = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^n (x_i - \bar{x})^2 \sum_{i=1}^n (y_i - \bar{y})^2}} \quad (37)$$

$$R^2 = \frac{n \sum_{i=1}^n x_i y_i - (\sum_{i=1}^n x_i)(\sum_{i=1}^n y_i)}{\sqrt{n(\sum_{i=1}^n x_i^2) - (\sum_{i=1}^n x_i)^2} \sqrt{n(\sum_{i=1}^n y_i^2) - (\sum_{i=1}^n y_i)^2}} \quad (38)$$

Where x_i , y_i , $\bar{x}$, $\bar{y}$ and n are observed data, estimated data, mean of observed data, mean of estimated data and number of data, respectively.

5. Results and Discussion

In this study, a network based on artificial intelligence technique was proposed for energy and thermal modeling of solar Dish/Stirling system. The network was proposed instead of the mathematical modeling by considering the major design parameters of the solar dish/Stirling system. The data presented in this study can be employed for training any other AI methods and easily used for the energy and thermal analysis of the system as described in Fig. 5. In this section, the effect of input variables of the network over the targets is investigated. Then, the performance prediction of the implemented AI methods for the energy and thermal assessing of the system is appraised.

5.1. Effect of Input Variables on the Targets

5.1.1. Working gas specific constant

Figure 8 depicts the influence of the working gas of the Stirling engine on mean yearly power versus hour of the day (for the ratio of focal point to dish diameter (f/d) of 0.5). The working gas were air ($R_{gas} = 287.0 \text{ J/kg K}$), nitrogen ($R_{gas} = 298.7 \text{ J/kg K}$) and helium ($R_{gas} = 2077.1 \text{ J/kg K}$). The gas specific constant is given by the universal gas constant, divided by the molar mass of gas, thus each particular gas has a different value. Gases with a high amount of gas constant (low molar mass) have high specific heat and low viscosity resulting in high heat capacity and less viscous losses. For this reason, in Fig. 8, it can be observed that for high concentration factor (and high temperature of system), the helium is the best working gas. However, the gas properties also depend on temperature, and for low temperatures due to low concentration factor, the trend is inverse, the helium has a less performance compared to air and nitrogen. The air and nitrogen have the similar behavior in all temperatures due to having similar gas specific constant.

Fig. 8. The effect of gas specific constant on the power of solar Dish/Stirling system.

5.1.2. Geometric concentrating factor

For the solar dish/Stirling collector by air as working gas and the ratio of focal point to dish diameter (f/d) as 0.5, the effect of concentration ratio on the targets was appraised (Fig. 9). The solar dish/Stirling system produces more electrical power when solar radiation increases. This generated power for higher values of the geometric concentrating factor (concentration ratio) increases as well (Fig. 9-a). By increasing the concentrating ratio, the magnitudes of the expansion chamber temperature (T_{HCTS}) (Fig. 9-b), global efficiency (Fig. 9-c), Q_E (Fig. 9-d) and engine speed (Fig. 9-e) increases in all cases.

a. Power generation (W)

b. T_{HCTS} (K)

c. Global efficiency

d. Heat transfer (W)

e. n (rps)

Fig. 9. Variation of the power generation (a), T_{HCTS} (b), global efficiency (c), heat transfer (d) and n (e) versus solar radiation in different concentrating ratios.

5.1.3. The ratio of focal point to receiver diameter

The solar Dish by concentrating ratio of 3000 and working gas of air by different values of the f/d was investigated and the results presented in Fig. 10. The results show that the power generation by the solar collector for $f/d=0.65$ is higher than 0.5 and 0.8 (Fig. 10-a). In addition, a slight increase is seen for T_{HCTS} (Fig. 10-b), global efficiency (Fig. 10-c), Q_E (Fig. 14-d) and engine speed (Fig. 10-e) by increasing the f/d .

Fig. 10. Variation of the power generation (a), T_{HCTS} (b), global efficiency (c), heat transfer (d) and n (e) versus solar radiation for various f/d .

5.2. Artificial Intelligence Modeling

In this section, the power generation of the system, T_{HCTS} , global efficiency, Q_E and engine speed of the solar dish/Stirling system are presented for the best configuration determined in the previous section: $CR=12000$, $f/d=0.65$ and helium (Figs. 11, 13, 15, 17, 20). In addition, different AI techniques were developed and trained for predicting these outputs of the solar dish/Stirling system in a wide range of input parameters and various configurations.

5.2.1. Power Generation

Figure 11 shows the produced power by the solar dish/Stirling system with configuration of CR=12000, $f/d=0.65$ and helium as working gas within a year in the case study region. For this configuration of the system, the produced power with an intermittent behavior varies between 0 and 2000 W.

Fig. 11. Power generation by the solar Stirling system with CR=12000, $f/d=0.65$, and helium as working gas for one year. In (a), power generation around the noon time of each day is shown, and in (b), power generation for the day 189 of the year is shown.

Table 1 demonstrates the prediction accuracy of the developed AI techniques for predicting the power generation of the solar-powered Stirling engine system. The intelligent methods were developed in Matlab software. Several trials were conducted to obtain the maximum precision of each method.

GMDH: In the current study GMDH type neural network that has been employed by the other researchers for modeling solar dish/Stirling system was implemented to compare with the prediction performance of the developed hybrid methods. GMDH was trained with the maximum number of neurons in a layer of 20, maximum number of layers of 25 and selection pressure of 0.7. The statistical indices (RMSE, R and R^2) for predicting the power generation of the system were obtained as 237.6581 (W), 0.9124 and 0.8324, respectively (for the test sample). These conclusions show that the GMDH neural network operates relatively well for forecasting the power generation, as can be observed in Fig. 12.

MLP-GA: Two evolutionary algorithms (PSO and GA) were integrated into MLP method to obtain the optimum network structure employed in the prediction process. The simulations have reported that the

statistical metrics for forecasting the produced power by MLP-GA are RMSE=214.248 (W), R=0.9270 and $R^2=0.8593$, for the test data. The testing stage of MLP-GA was plotted in Fig. 12. The MLP-GA was constructed by considering the following design parameters: number of neurons in the hidden layer: 25, transfer function: “*tansig*”, maximum generations: 500, population size: 500.

MLP-PSO: In the current investigation, the MLP-PSO method was constructed based on the following algorithm’s parameters: number of neurons in the hidden layer: 25, transfer function: “*tansig*”, number of hidden layers: 1, maximum iteration: 500, cognition coefficient (C_1): 2, social coefficient: $4-C_1$, swarm size: 500. Table 3 reported the statistical indicator for the MLP-PSO as RMSE=184.296 (W), R=0.9554 and $R^2=0.9127$. These statistical indicators illustrate that MLP-PSO works better than MLP-GA, GMDH and ANFIS-GA to estimate the power generation by the solar system as can be observed in Fig. 12.

ANFIS-PSO: Particle swarm optimization algorithm was combined with ANFIS method as a hybrid method to improve the performance prediction of the base method. The statistical metrics to estimate the produced power by the ANFIS method were obtained as RMSE=225.683 (W), R=0.9228 and $R^2=0.8515$. We applied the PSO and GA evolutionary algorithms to improve the performance of the ANFIS method. ANFIS-PSO method was implemented by: number of clusters: 10, maximum iteration: 500, personal learning coefficient: 1, global learning coefficient: 2, inertia weight: 1, inertia weight damping ratio: 0.99. To find out the performance of the ANFIS-PSO method by considering different number of populations, the statistical indicators (RMSE, R and R^2) during training and testing were evaluated. The ANFIS-PSO method by 500 populations had the lowest statistical errors. The testing phase of the ANFIS-PSO was presented in Fig. 12. It can be clearly observed that the real data and predicted data by the ANFIS-PSO method agree with each other to a large extent for test dataset. In addition, this method shows the highest prediction accuracy compared to other AI techniques.

ANFIS-GA: Table 1 indicates performance prediction of ANFIS-GA method to forecast the produced power by the solar system. This method was developed based on the following structure: number of clusters: 10, maximum iteration: 500, number of populations: 500, crossover percentage: 0.7, mutation percentage: 0.2, mutation rate: 0.1. Moreover, performance assessment of this prediction shows that the ANFIS-GA outperforms the MLP-GA and GMDH. Testing stage of the ANFIS-GA was plotted in Fig. 16 and compared with other developed methods.

Table 1. Statistical indices for predicting the power generation by AI methods.

Model	RMSE (W)		R		R^2	
	Train	Test	Train	Test	Train	Test
ANFIS-GA	193.1055	193.955	0.9435	0.9420	0.8901	0.8873
ANFIS-PSO	143.4111	155.6449	0.9692	0.9630	0.9393	0.9273
MLP-GA	214.248	223.6152	0.9270	0.9336	0.8593	0.8716
MLP-PSO	173.4963	184.296	0.9486	0.9554	0.8998	0.9127
GMDH	234.4773	237.6581	0.9150	0.9124	0.8372	0.8324

Fig. 12. The power generation prediction by intelligent methods, test stage of each model: (a) MLP-GA, (b) MLP-PSO, (c) ANFIS-GA, (d) GMDH, (e) ANFIS-PSO.

5.2.2. The engine speed

Figure 13 illustrates the engine speed for the solar dish/Stirling system with CR of 12000, f/d of 0.65 and working gas of helium; for sunny hours during a year. The engine speed is an important parameter for determining the energy and thermal characteristics of the solar collector. This graph shows that the engine speed has a behavior between 1320 (rps) and 1420 (rps). According to Caetano et al. [57] the engine torque is directly proportional to the engine speed and the output power. Assuming the engine speed is practically constant during a day, it is possible to affirm that the torque and power have the same behavior.

Fig. 13. The speed of Stirling engine for the collector by $CR=12000$, $f/d=0.65$ and working gas of helium. In (a), the engine speed around the noon time of each day is plotted, and in (b), the engine speed for the day 189 of the year is plotted.

Table 2 summarizes the performance prediction of the developed intelligent methods for forecasting the engine speed by considering the disparate input variables. As can be observed in the table, the developed intelligent methods can meticulously predict the engine speed with a high correlation and determination coefficients and low RMSE. Among them, the ANFIS-PSO possesses the lowest value of RMSE for the test data as 5.5864 (rps). The test data for this prediction for each intelligent method was plotted in Fig. 14.

Table 2. Proficiency prediction of the intelligent methods for modeling the engine speed.

Model	RMSE (rps)		R		R ²	
	Train	Test	Train	Test	Train	Test
ANFIS-GA	9.8477	9.7595	0.9994	0.9994	0.9988	0.9988
ANFIS-PSO	5.3667	5.5864	0.9998	0.9998	0.9996	0.9996
MLP-GA	15.1066	15.1088	0.9986	0.9986	0.9972	0.9972
MLP-PSO	10.8648	11.1674	0.9992	0.9993	0.9984	0.9986
GMDH	11.1093	10.7947	0.9992	0.9992	0.9984	0.9984

Fig. 14. Test data of the intelligent methods for modeling of the engine speed: (a) ANFIS-GA, (b) MLP-GA, (c) MLP-PSO, (d) GMDH, (e) ANFIS-PSO.

5.2.3. Expansion chamber temperature

For the considered solar dish/Stirling system with $CR=12000$, $f/d=0.65$ and working gas=helium, the expansion chamber temperature in an alternating variation ranges from 400 K to 1200 K, as presented in Fig. 15. This intermittency shows that modeling the behavior of the expansion chamber temperature is a sophisticated task. Hence, the intelligent methods based on AI approach were implemented to catch the

non-linear behavior between the input variables to simulate the manner of the expansion chamber temperature. Table 3 represents the assessment of the intelligent methods for this simulation. The ANFIS-PSO is shown the uttermost precision with RMSE=47.4419 K, R=0.9653 and $R^2=0.9318$. The testing phase of this simulation for the developed intelligent methods are presented in Fig. 16.

Fig. 15. The expansion chamber temperature for the solar Dish/Stirling system in entire year. In (a), the expansion chamber temperature around the noon time of each day is depicted, and in (b), the expansion chamber temperature for the day 189 of the year is depicted.

Table 3. Assessment of intelligent methods employed for modeling the expansion chamber temperature.

Model	RMSE (K)		R		R ²	
	Train	Test	Train	Test	Train	Test
ANFIS-GA	60.7809	58.9324	0.9432	0.9470	0.8896	0.8968
ANFIS-PSO	44.6641	47.4419	0.9694	0.9653	0.9397	0.9318
MLP-GA	62.8519	63.2779	0.9476	0.9485	0.8979	0.8996
MLP-PSO	53.0303	51.2222	0.9598	0.9576	0.9212	0.9169
GMDH	72.2259	72.4815	0.91856	0.9166	0.8437	0.8401

input variables and different design structures. According to the statistical indices reported in Table 4, the ANFIS-PSO operated better than the other developed methods to simulate the manner of global efficiency. Figure 18 depicts the test data of the intelligent methods for predicting the global efficiency of the solar collector.

Fig. 17. Global efficiency of the solar Dish/Stirling system during one year. In (a), the global efficiency around the noon time of each day is illustrated, and in (b), the global efficiency for the day 189 of the year is illustrated.

Table 4. Evaluation of the intelligent methods for predicting the global efficiency.

Model	RMSE (W)		R		R ²	
	Train	Test	Train	Test	Train	Test
ANFIS-GA	0.0271	0.0270	0.9396	0.9399	0.8828	0.8834
ANFIS-PSO	0.0249	0.0248	0.9498	0.9486	0.9021	0.8998
MLP-GA	0.0282	0.0270	0.9422	0.9364	0.8877	0.8768
MLP-PSO	0.0243	0.0250	0.9490	0.9527	0.9006	0.9076
GMDH	0.0323	0.0313	0.9130	0.9183	0.8335	0.8432

Fig. 18. Test data of the developed intelligent methods for predicting the global efficiency: (a) ANFIS-GA, (b) MLP-GA, (c) MLP-PSO, (d) GMDH, (e) ANFIS-PSO.

Figure 19 represents the ANFIS-PSO decision surfaces for modeling of global efficiency using different input variables. Indeed, these surfaces show how the ANFIS-PSO make a decision for prediction of the global efficiency by different geometric concentration factor, working gas specific constant, the ratio of focal point to dish diameter and solar radiation. In addition, in this simulation, hours of day were considered as an input variable to improve the performance prediction of the networks. Based on the decision surfaces,

the global efficiency slightly increases when working gas specific constant increases. The figure shows that the global efficiency has a tendency to increase by enhancing the ratio of focal point to dish diameter. Moreover, increasing the geometric concentration factor moderately raises global efficiency. As expected, the global efficiency by increasing solar radiation significantly increases (from 400 to 1000 (W/m^2)).

Fig. 19. ANFIS-PSO decision surfaces for simulating the global efficiency: (a) global efficiency vs solar radiation and hour of day, (b) global efficiency vs CR and R_{gas} , (c) global efficiency vs f/d and R_{gas} .

5.2.5. Stirling cycle input heat (Q_E)

For the solar dish/Stirling system ($\text{CR}=12000$, $f/d=0.65$, working gas=helium), the imputed heat to run the Stirling cycle for one year is shown in Fig. 20. The values of Q_E change from 0 to 7000 W. This manner for different conditions was modeled by intelligent methods. Table 5 epitomizes the performance evaluation of the intelligent methods for predicting the Stirling cycle input heat. The ANFIS-PSO outperforms the ANFIS-GA, GMDH, MLP-GA and MLP-PSO for modeling the Q_E according to the statistical indicators obtained as $\text{RMSE}=601.6007$ (W), $R=0.9708$ and $R^2=0.9424$, for the testing sample. Test stage of the intelligent methods for forecasting the Q_E was presented in Fig. 21.

Fig. 20. Stirling cycle input heat for the solar Dish with $CR=12000$, $f/d=0.65$ and working gas=helium. In (a), the Stirling cycle input heat around the noon time of each day is demonstrated, and in (b), the Stirling cycle input heat for the day 189 of the year is demonstrated.

Table 5. Performance assessment of the intelligent methods for predicting the Q_E .

Model	RMSE (W)		R		R ²	
	Train	Test	Train	Test	Train	Test
ANFIS-GA	944.0884	951.1842	0.9254	0.9238	0.8563	0.8534
ANFIS-PSO	614.3244	601.6007	0.9687	0.9708	0.9383	0.9424
MLP-GA	1243.1478	1250.8564	0.8672	0.8668	0.7520	0.7513
MLP-PSO	1014.0519	980.9147	0.9227	0.9170	0.8513	0.8408
GMDH	1044.9627	1046.9156	0.9065	0.9085	0.8217	0.8253

Fig. 21. Testing stage of the intelligent methods for forecasting Q_E : (a) ANFIS-GA, (b) MLP-GA, (c) GMDH, (d) MLP-PSO, (e) ANFIS-PSO.

6. Conclusions

In recent years, development in renewable energy systems for power generation has accelerated. Combining a parabolic dish with Stirling engine has been introduced as one of the new, sustainable and efficient ways for power generation from solar energy. For its high efficiency, the parabolic dish is widely used when compared to the other technologies of solar concentration, as well as for its practicality in the implementation of solar tracking technology. Produced power by solar dish/Stirling depends on many

parameters such as geometric concentration factor, solar radiation, working fluid of Stirling engine, disk diameter and focal point. The maximum power was found for configuration of $CR=12000$, $f/d=0.65$ and helium.

Modeling of Stirling solar collector due to intermittency of solar radiation as well as considering many design parameters is complicated. Based on the literature, GMDH neural network and ANFIS method were two methods of artificial intelligence that have been widely employed for modeling of the solar-powered Stirling engine collector. In this study, we developed four hybrid methods (ANFIS-PSO, ANFIS-GA, MLP-PSO and MLP-GA) for modeling of the Stirling-solar collector.

The proposed network can simulate the energy and thermal behavior of the solar system and can be used instead of the mathematical modeling in other study regions with different geometry, as the data source was attached to this paper. Each intelligent method can be trained with the dataset and then used for energy and thermal modeling of the system. The main conclusions of this research are as follows:

- **Power generation:** the power generation of the solar dish/Stirling system increased when the working gas specific constant decreased, the geometric concentration factor increased and the solar radiation enhanced. The utmost produced power was achieved for the ratio of focal point to dish diameter of 0.65. This alternate movement was simulated by the intelligent methods in which the ANFIS-PSO was reported uttermost proficiency for all cases.
- **Expansion chamber temperature:** The expansion chamber temperature had a tendency to increase by decreasing the working gas specific constant, increasing the geometric concentration factor, ratio of focal point to dish diameter and solar radiation. This dynamic manner was also modelled with high accuracy through intelligent methods.
- **Global efficiency:** The solar dish/Stirling global efficiency improved with an increase in the geometric concentrating factor, f/d and solar radiation and declined with a decrease in working gas specific constant. The ANFIS-PSO predicted the behavior of the global efficiency under different configurations with $RMSE=0.025$, $R=0.9527$ and $R^2=0.9076$.
- **Stirling cycle input heat:** For the solar Dish/Stirling system the heat imputed to run the Stirling cycle for working gas of helium was higher than nitrogen and air respectively. For the other input variables, the Q_E remained almost constant. For this simulation, the statistical indicators for the ANFIS-PSO were obtained as $RMSE=601.6007$ W, $R=0.9708$, $R^2=0.9424$.
- **Engine speed:** The engine speed varied between 1320 (rps) and 1420 (rps) and it increased by increasing the working gas specific constant, f/d , solar radiation and geometric concentration factor. The intelligent methods predicted precisely the engine speed with minimum values of RMSE for the training and testing samples and maximum values of correlation and determination coefficients.

Acknowledgments

Ali Khosravi and Sanna Syri would like to express their appreciation to Aalto University (Department of Mechanical Engineering, grant no. Postdoc/T21201) for the financial support of the project. The other authors acknowledge from CAPES, FAPEMIG and CNPq, for the financial support of the research.

References

- [1] Global Warming of 1.5 °C — n.d. <https://www.ipcc.ch/sr15/> (accessed January 21, 2019).
- [2] Khosravi A, Koury RNN, Machado L, Pabon JGG. Energy, exergy and economic analysis of a hybrid renewable energy with hydrogen storage system. *Energy* 2018;148:1087–102. doi:10.1016/j.energy.2018.02.008.
- [3] Khosravi A, Syri S, El Haj Assad M, Malekan M. Thermodynamic and Economic Analysis of a Hybrid Ocean Thermal Energy Conversion/Photovoltaic System with Hydrogen-Based Energy Storage System. *Energy* 2019;172:304–19.
- [4] Barreto G, Canhoto P. Modelling of a Stirling engine with parabolic dish for thermal to electric conversion of solar energy. *Energy Convers Manag* 2017;132:119–35. doi:10.1016/J.ENCONMAN.2016.11.011.
- [5] Hachem H, Gheith R, Aloui F, Ben Nasrallah S. Technological challenges and optimization efforts of the Stirling machine: A review. *Energy Convers Manag* 2018;171:1365–87. doi:10.1016/J.ENCONMAN.2018.06.042.
- [6] Karabulut H, Çınar C, Oztürk E, Yücesu HS. Torque and power characteristics of a helium charged Stirling engine with a lever controlled displacer driving mechanism. *Renew Energy* 2010;35:138–43. doi:10.1016/J.RENENE.2009.04.023.
- [7] Balcombe P, Rigby D, Azapagic A. Environmental impacts of microgeneration: Integrating solar PV, Stirling engine CHP and battery storage. *Appl Energy* 2015;139:245–59. doi:10.1016/J.APENERGY.2014.11.034.
- [8] Chahartaghi M, Sheykhi M. Thermal modeling of a trigeneration system based on beta-type Stirling engine for reductions of fuel consumption and pollutant emission. *J Clean Prod* 2018;205:145–62. doi:10.1016/J.JCLEPRO.2018.09.008.
- [9] Aksoy F, Karabulut H, Çınar C, Solmaz H, Özgören YÖ, Uyumaz A. Thermal performance of a Stirling engine powered by a solar simulator. *Appl Therm Eng* 2015;86:161–7. doi:10.1016/J.APPLTHERMALENG.2015.04.047.
- [10] Kong XQ, Wang RZ, Huang XH. Energy efficiency and economic feasibility of CCHP driven by stirling engine. *Energy Convers Manag* 2004;45:1433–42. doi:10.1016/J.ENCONMAN.2003.09.009.
- [11] Alanne K, Söderholm N, Sirén K, Beausoleil-Morrison I. Techno-economic assessment and optimization of Stirling engine micro-cogeneration systems in residential buildings. *Energy Convers Manag* 2010;51:2635–46. doi:10.1016/J.ENCONMAN.2010.05.029.
- [12] Bonilla JJ, Blanco JM, López L, Sala JM. Technological recovery potential of waste heat in the industry of the Basque Country. *Appl Therm Eng* 1997;17:283–8. doi:10.1016/S1359-4311(96)00024-5.
- [13] Kongtragool B, Wongwises S. A review of solar-powered Stirling engines and low temperature differential Stirling engines. *Renew Sustain Energy Rev* 2003;7:131–54. doi:10.1016/S1364-0321(02)00053-9.
- [14] Punathanam V, Kotecha P. Effective multi-objective optimization of Stirling engine systems. *Appl Therm Eng* 2016;108:261–76. doi:10.1016/J.APPLTHERMALENG.2016.07.029.
- [15] Ni M, Shi B, Xiao G, Peng H, Sultan U, Wang S, et al. Improved Simple Analytical Model and experimental study of a 100 W β -type Stirling engine. *Appl Energy* 2016;169:768–87. doi:10.1016/J.APENERGY.2016.02.069.
- [16] Pavlovic S, Daabo AM, Bellos E, Stefanovic V, Mahmoud S, Al-Dadah RK. Experimental and numerical investigation on the optical and thermal performance of solar parabolic dish and corrugated spiral cavity receiver. *J Clean Prod* 2017;150:75–92. doi:10.1016/J.JCLEPRO.2017.02.201.
- [17] Ghalamchi M, Kasaeian A, Ghalamchi M. Experimental study of geometrical and climate effects

524 on the performance of a small solar chimney. *Renew Sustain Energy Rev* 2015;43:425–31.
525 doi:10.1016/J.RSER.2014.11.068.

526 [18] Desai NB, Bandyopadhyay S. Line-focusing concentrating solar collector-based power plants: a
527 review. *Clean Technol Environ Policy* 2017;19:9–35. doi:10.1007/s10098-016-1238-4.

528 [19] Okoroigwe E, Madhlopa A. An integrated combined cycle system driven by a solar tower: A
529 review. *Renew Sustain Energy Rev* 2016;57:337–50. doi:10.1016/J.RSER.2015.12.092.

530 [20] Li Y, Liao S, Liu G. Thermo-economic multi-objective optimization for a solar-dish Brayton
531 system using NSGA-II and decision making. *Int J Electr Power Energy Syst* 2015;64:167–75.
532 doi:10.1016/J.IJEPES.2014.07.027.

533 [21] Hafez AZ, Soliman A, El-Metwally KA, Ismail IM. Solar parabolic dish Stirling engine system
534 design, simulation, and thermal analysis. *Energy Convers Manag* 2016;126:60–75.
535 doi:10.1016/J.ENCONMAN.2016.07.067.

536 [22] Yaqi L, Yaling H, Weiwei W. Optimization of solar-powered Stirling heat engine with finite-time
537 thermodynamics. *Renew Energy* 2011;36:421–7. doi:10.1016/J.RENENE.2010.06.037.

538 [23] Sharma JK, Dang A, Garg HP, Mathur SS. Solar flux distributions from circular cylindrical
539 concentrators. *Sol Energy* 1983;30:507–12. doi:10.1016/0038-092X(83)90062-2.

540 [24] Jeter SM. The Distribution of Concentrated Solar Radiation in Paraboloidal Collectors. *J Sol*
541 *Energy Eng* 1986;108:219. doi:10.1115/1.3268096.

542 [25] Reddy KS, Natarajan SK, Veershetty G. Experimental performance investigation of modified
543 cavity receiver with fuzzy focal solar dish concentrator. *Renew Energy* 2015;74:148–57.
544 doi:10.1016/J.RENENE.2014.07.058.

545 [26] Maghrabi AH. Parameterization of a simple model to estimate monthly global solar radiation based
546 on meteorological variables, and evaluation of existing solar radiation models for Tabouk, Saudi
547 Arabia. *Energy Convers Manag* 2009;50:2754–60. doi:10.1016/J.ENCONMAN.2009.06.024.

548 [27] Zhang J, Zhao L, Deng S, Xu W, Zhang Y. A critical review of the models used to estimate solar
549 radiation. *Renew Sustain Energy Rev* 2017;70:314–29. doi:10.1016/J.RSER.2016.11.124.

550 [28] Chen J, Yan Z, Chen L, Andresen B. Efficiency bound of a solar-driven stirling heat engine system.
551 *Int J Energy Res* 1998;22:805–12. doi:10.1002/(SICI)1099-114X(199807)22:9<805::AID-
552 ER404>3.0.CO;2-K.

553 [29] Liao T, Lin J. Optimum performance characteristics of a solar-driven Stirling heat engine system.
554 *Energy Convers Manag* 2015;97:20–5. doi:10.1016/J.ENCONMAN.2015.03.027.

555 [30] Beltran R, Velazquez N, Espericueta AC, Saucedo D, Perez G. Mathematical model for the study
556 and design of a solar dish collector with cavity receiver for its application in Stirling engines. *J*
557 *Mech Sci Technol* 2012;26:3311–21. doi:10.1007/s12206-012-0801-0.

558 [31] Ahmadi MH, Dehghani S, Mohammadi AH, Feidt M, Barranco-Jimenez MA. Optimal design of a
559 solar driven heat engine based on thermal and thermo-economic criteria. *Energy Convers Manag*
560 2013;75:635–42. doi:10.1016/J.ENCONMAN.2013.07.078.

561 [32] Ahmadi MH, Ahmadi MA, Mohammadi AH, Feidt M, Pourkiaei SM. Multi-objective optimization
562 of an irreversible Stirling cryogenic refrigerator cycle. *Energy Convers Manag* 2014;82:351–60.
563 doi:10.1016/J.ENCONMAN.2014.03.033.

564 [33] Hooshang M, Askari Moghadam R, Alizadeh Nia S, Masouleh MT. Optimization of Stirling engine
565 design parameters using neural networks. *Renew Energy* 2015;74:855–66.
566 doi:10.1016/J.RENENE.2014.09.012.

567 [34] Ahmadi M, Ahmadi M-A, Mehrpooya M, Rosen M, Ahmadi MH, Ahmadi M-A, et al. Using
568 GMDH Neural Networks to Model the Power and Torque of a Stirling Engine. *Sustainability*
569 2015;7:2243–55. doi:10.3390/su7022243.

570 [35] Karaboga D, Kaya E. Adaptive network based fuzzy inference system (ANFIS) training
571 approaches: a comprehensive survey. *Artif Intell Rev* 2018;1–31. doi:10.1007/s10462-017-9610-

572 2.

573 [36] Özgören YÖ, Çetinkaya S, Sarıdemir S, Çiçek A, Kara F. Predictive modeling of performance of a
574 helium charged Stirling engine using an artificial neural network. *Energy Convers Manag*
575 2013;67:357–68. doi:10.1016/J.ENCONMAN.2012.12.007.

576 [37] Ahmadi MH, Ahmadi MA, Sadatsakkak SA, Feidt M. Connectionist intelligent model estimates
577 output power and torque of stirling engine. *Renew Sustain Energy Rev* 2015;50:871–83.
578 doi:10.1016/J.RSER.2015.04.185.

579 [38] Loni R, Kasaeian A, Shahverdi K, Askari Asli-Ardeh E, Ghobadian B, Ahmadi MH. ANN model
580 to predict the performance of parabolic dish collector with tubular cavity receiver. *Mech Ind*
581 2017;18:408. doi:10.1051/meca/2017016.

582 [39] Alata M, Al-Nimr MA, Qaroush Y. Developing a multipurpose sun tracking system using fuzzy
583 control. *Energy Convers Manag* 2005;46:1229–45. doi:10.1016/J.ENCONMAN.2004.06.013.

584 [40] Pereira EB, Martins FR, Abreu SL De, Rüther R. *Atlas Brasileiro da Energia Solar*. 2.ed. São José
585 Dos Campos - Brazil: INPE; 2017.

586 [41] Luiz EW, Martins FR, Pereira EB, Schuch NJ, Favera ACD, Ceconi M. Solar irradiation numerical
587 modeling as alternative method in evaluating of available energy potential. *Rev Geográfica*
588 *Acadêmica* 2010;4:41–52.

589 [42] Download free solar resource maps | Solargis n.d. [http://solargis.com/products/maps-and-gis-](http://solargis.com/products/maps-and-gis-data/free/download/iran)
590 [data/free/download/iran](http://solargis.com/products/maps-and-gis-data/free/download/iran) (accessed July 24, 2017).

591 [43] Duffie JA, Beckman WA. *Solar engineering of thermal processes*. John Wiley & Sons; 2013.

592 [44] Sandoval OR, Castro B, Ungaretti M, García JJ, Molina R. Modelling , simulation and thermal
593 analysis of a solar dish / Stirling system : A case study in Natal , Brazil. *Energy Convers Manag*
594 2019;181:189–201. doi:10.1016/j.enconman.2018.12.005.

595 [45] Barreto G, Canhoto P, Collares-Pereira M. Three-dimensional modelling and analysis of solar
596 radiation absorption in porous volumetric receivers. *Appl Energy* 2018;215:602–14.
597 doi:10.1016/j.apenergy.2018.02.065.

598 [46] Popiel CO. Free Convection Heat Transfer from Vertical Slender Cylinders: A Review. *Heat Transf*
599 *Eng* 2008;29:521–36. doi:10.1080/01457630801891557.

600 [47] Sripakagorn A, Srikam C. Design and performance of a moderate temperature difference Stirling
601 engine. *Renew Energy* 2011;36:1728–33. doi:10.1016/j.renene.2010.12.010.

602 [48] Ivakhnenko A. Polynomial theory of complex systems. *IEEE Trans Syst Man Cybern* 1971;1:364–
603 78.

604 [49] Rostami A, Hemmati-Sarapardeh A, Karkevandi-Talkhooncheh A, Husein MM, Shamshirband S,
605 Rabczuk T. Modeling heat capacity of ionic liquids using group method of data handling: A hybrid
606 and structure-based approach. *Int J Heat Mass Transf* 2019;129:7–17.
607 doi:10.1016/J.IJHEATMASSTRANSFER.2018.09.057.

608 [50] Khosravi A, Pabon JJGJG, Koury R.N.N, Machado L. Using machine learning algorithms to predict
609 the pressure drop during evaporation of R407C. *Appl Therm Eng* 2018;133:361–70.
610 doi:10.1016/j.applthermaleng.2018.01.084.

611 [51] Khosravi A, Nunes RO, Assad MEH, Machado L. Comparison of artificial intelligence methods in
612 estimation of daily global solar radiation. *J Clean Prod* 2018;194:342–58.
613 doi:10.1016/J.JCLEPRO.2018.05.147.

614 [52] Khosravi A, Machado L, Nunes RO. Estimation of density and compressibility factor of natural gas
615 using artificial intelligence approach. *J Pet Sci Eng* 2018;168:201–16.
616 doi:10.1016/j.petrol.2018.05.023.

617 [53] Malekan M, Khosravi A. Investigation of Convective Heat Transfer of Ferrofluid using CFD
618 Simulation and Adaptive Neuro-Fuzzy Inference System Optimized with Particle Swarm
619 Optimization Algorithm. *Powder Technol* 2018;333:364–76.

- [54] Oliveira M V., Schirru R. Applying particle swarm optimization algorithm for tuning a neuro-fuzzy inference system for sensor monitoring. *Prog Nucl Energy* 2009;51:177–83. doi:10.1016/j.pnucene.2008.03.007.
- [55] Khosravi A, Machado L, Nunes RO. Time-series prediction of wind speed using machine learning algorithms: A case study Osorio wind farm, Brazil. *Appl Energy* 2018;224:550–66. doi:10.1016/j.apenergy.2018.05.043.
- [56] Stine WB, Diver RB. A compendium of solar dish/Stirling technology. Albuquerque, NM, and Livermore, CA (United States): 1994. doi:10.2172/10130410.
- [57] Caetano BC, Lara IF, Borges MU, Sandoval OR, Valle RM. A novel methodology on beta-type Stirling engine simulation using CFD. *Energy Convers Manag* 2019;184:510–20. doi:10.1016/j.enconman.2019.01.075.